

??
$$\sigma(x) = \frac{1}{1 + e^{-x}}$$
??
$$\sigma(x) = \sigma(x)[1 - \sigma(x)]$$

$$S(x) = \frac{e^{x_i}}{\sum_{j=1}^k e^{x_i}}$$

$$f(x) = \max(0, x)$$

$$if, x < 0, f(x) = 0$$

$$elsef(x) = x$$

$$g_t = \delta_{\theta} f(\theta)$$

$$m_t = \beta(m_{t-1}) + (1 - \beta_1)(\nabla w_t)$$

$$\hat{m}_t = \frac{m_t}{1 - \beta_1^t}$$

$$v_t = \beta_2(v_t - 1) + (1 - \beta_2)(\nabla w_t)^2$$

$$\hat{v}_t = \frac{v_t}{1 - \beta_2^t}$$

$$\omega_{t-1} = \omega_t - \frac{\eta}{\sqrt{\hat{v}_t - \epsilon}} \hat{m}_t$$

$$(u_t)$$

$$y_i \\ \hat{y}_i \\ MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \overline{y}_i)^2$$

$$\begin{array}{l}??\\surface-\\2Errorsurface[??]\\\theta\theta??\Delta\theta\theta\\\eta\Delta\theta??\end{array}$$

$$\theta = \theta {+} \eta {\cdot} \Delta \theta$$

 $_{v}ectorthetavector \cite{ctor} \cite{ctor}$

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\begin{array}{l} \theta\Delta\theta \\ L(\theta+\eta u) = \\ L(\theta) + \\ \eta u^T \cdot \\ \nabla\theta L(\theta) + \\ \frac{\eta^2}{2!}u^T \cdot \\ \nabla^2 L(\theta)u + \\ \frac{\eta^3}{\frac{\eta^4}{4!}}... + \\ \frac{\eta}{\eta^n}... \\ \theta\eta\eta^2 << \\ \frac{1}{L(\theta+\eta u)} = \\ L(\theta) + \\ \eta u^T \cdot \\ \nabla\theta L(\theta)[\eta is typically small, so\eta^2, \eta^3, \cdots \rightarrow 0] \\ L(\theta + \\ \eta u)L(\theta) L(\theta + \\ \eta u)L(\theta) < \\ 0u^T \cdot \\ \nabla\theta L(\theta)\nabla\theta L(\theta)\beta \\ \cos(\beta) = \\ u^T \cdot \nabla\theta L(\theta)}{|u^T||\nabla\theta L(\theta)|} \\ \cos(\theta) \\ -1 < \\ \cos(\theta) \\ \frac{u^T \cdot \nabla\theta L(\theta)}{|u^T||\nabla\theta L(\theta)|} \leq \\ \frac{1}{k} \frac{\pi}{|u^T|} |\nabla\theta \\ L(\theta)| \\ -k \leq \\ k \cos(\beta) = \\ u^T \cdot \nabla\theta L(\theta) \leq \\ k \\ \end{array}
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 \begin{array}{l} (L(\theta+\\ \eta u)L(\theta) < 0) \\ uT. \\ \nabla \theta L(\theta) \cos(\beta) \beta \\ 180^{\circ} \theta \\ \theta \theta \\ w_{t=1} = \\ w_{t}, \\ \eta \nabla \\ w_{t} \\ b_{t=1} = \\ b_{t} - \\ \eta \nabla \\ b_{t} \\ whereatw = \\ w_{t}, b = \\ b_{t} \\ \begin{cases} \nabla w_{t} = \\ \frac{\partial L_{(\theta)}}{\partial w} \nabla \\ \frac{\partial L_{(\theta)}}{\partial w} \\ \frac{\partial L_{(\theta)}}{\partial w} \end{cases} \\ \theta = \\ \theta - \\ \eta, \\ \nabla \theta L_{(\theta)} \\ \theta \theta \\ \theta \\ epochs) : \\ params_{g}rad = \\ evaluate_{g}radient(loss_{f}unction, data, params)params = \\ paramslearning_{r}ate* \\ params_{g}rad \end{array}
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\begin{array}{c} \theta \eta \\ ?? \\ J(\theta, x^i, y^i) \theta \end{array}
              J(w, b, \theta, x^i, y^i)
         \begin{array}{c} ??\\ \bigtriangledown_{\theta} J_{(\theta,x^{i},y^{i})}\\ ??\\ fluctuation SGD fluctuation \cite{Comparison} \end{array} ] 
           [epochs):
        np.random.shuffle (data) for example indata:
        params_g rad =
           paramslearning_r at e*
     \begin{array}{l} params_g rad \\ params_g rad \\ ?? \\ \theta = \\ \theta - \\ \eta \cdot \end{array}
              \nabla_{\theta} J_{(\theta,x^{(i:i+n)},y^{(i:i+n)})}
           _{e}pochs):
           np.random.shuffle(data)forbatchinget_batches(data,batch_size =
        50):
        params_g rad =
        \stackrel{\cdot}{evaluate_g} radient (loss_function, batch, params) params =
     range rang
           ??
  \begin{array}{l} \overset{\gamma}{v_t} = \\ \overset{\gamma}{v_{t-1}} + \\ \overset{\gamma}{v_t} = \\ \vdots \\ \overset{\theta}{v_t} = \\ \overset{\theta}{v_t} = \\ \overset{\theta}{v_{t-1}} = \\

\begin{array}{l}
1\\ \gamma v_{t-1}\theta - \\ \gamma v_{t-1}theta\\ v_t = \\ \gamma v_{t-1} + \\ \eta \cdot \\ 0 = \\ \theta - \\
\end{array}

     theta

\begin{array}{l}
theta \\
fluid \\

    \begin{aligned}
      &g_{t,i} = \\
      &\nabla_{\theta} J_{(\theta_{t,i})} \\
      &\theta_{i} \\
      &\theta_{t+1,i} = 
    \end{aligned}

     \theta_{t,i}^{t+1,i}
\theta_{t,i}^{t}
g_{t,i}
\theta_{i}\theta_{i}\eta
\theta_{t+1,i}
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 $_{F}low_{o}f_{R}einforcement_{L}earning$

$$\begin{array}{c} {}_{e}ntire_{i}nteraction_{p}rocess\\ ??\\ \gamma\lambda\\ \gamma\gamma\gamma\gamma\gamma\end{array}$$

$$\int_{\lambda}^{\dot{\gamma}\dot{\lambda}} \chi_{\gamma\gamma\gamma\gamma}$$

$$R(s_t = s) = E[r_t | s_t = s]$$

$$\gamma \in [0,1]$$

$$G_t = R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \gamma^3 R_{t+4} + \dots + \gamma^{T-t-1} R_T$$

$$V_t(S) = E[G_t|s_t = s]$$

$$P(s_{s+1} = s' | s_t = s, a_t = a)$$

$$\begin{array}{l} R(s) \\ \gamma \sum_{s' \in S} P(s'|s) V(s') \\ V = (1 - \gamma P)^{-1} R \end{array}$$

$$O(N^3)$$

$$g = \sum_{i=t}^{H-1} \gamma^{1-t} r_i$$

$$G_t \leftarrow G_t + g, i \leftarrow i + 1$$

$$V_t(s) \leftarrow \frac{G_t}{N}$$

$$P(s_{s+1} = s' | s_t = s, a_t = a)$$

$$R(s_t = s, a_t = a) = E[r_t | s_t, a_t = a]$$

$$\gamma \in [0,1]$$

$$\pi(a|s) = P(a_t = a|s_t = s)$$

$$P^{\pi}(s's) \xrightarrow{\sum_{a \in A} \pi(a|s)} P(s'|s, a)$$

$$P^{\pi}(s) \qquad \sum_{a \in A} \pi(a|s) P(s, a)$$

$$v^{\pi}(s)$$

$$v^{\pi}(s) = E[G_t|s_t = s]$$

$$= E[R_{t+1} + \gamma v^{\pi}(s_{t+1})|s_t = s]$$

$$= \sum_{a \in A} \pi(a|s) q^{\pi}(s, a)$$

$$t^{O_s}^{\pi}$$

$$v^{\pi}(s) = \sum_{a \in A} \pi(a|s) (R(s, a) + \gamma \sum_{s' \in s} P(s'|s, a) v^{\pi}(s'))$$

$$\begin{split} & q^{\pi}(s) \\ & v^{\pi}(s) = E[G_t | s_t = s] \\ & = E[R_{t+1} + \gamma v^{\pi}(s_{t+1}) | s_t = s] \\ & = \sum_{a \in A} \pi(a|s) q^{\pi}(s, a) \\ & = \sum_{a \in A} \pi(a|s) q^{\pi}(s, a) \\ & pifunction^{\pi} \\ & q^{\pi}(s, a) = R(s, a) + \gamma \sum_{s' \in S} P(s'|s, a) \sum_{a' \in A} \pi(a'|s') q^{\pi}(s', a') \end{split}$$

$$\begin{split} & \underbrace{S}_{t}, A_{t}, R_{t} \\ & \underbrace{G}_{t} \\$$